Journal of Innovative Image Processing (ISSN: 2582-4252)
www.irojournals.com/iroiip/

A Comprehensive Overview of Teeth Image Segmentation Using Deep Learning Approaches

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Abstract

This work primarily focuses on convolutional neural networks (CNNs) and quantitatively analyzes dental images using deep learning models. Tooth separation is considerably improved when X-rays and computer images are used for dental procedure planning, diagnosis, and treatment. The aim of the research is to examine the performance of cutting-edge segmentation models on publicly available dental image datasets. The study demonstrates that CNN-based techniques consistently outperformed conventional machine learning models in terms of accuracy and robustness, especially when compared to noisy and low contrast images. According to these findings, it is possible to create efficient computer-aided detection (CAD) tools that will help dentists diagnose patients. By using Explainable AI, we can improve confidence and simplify the usage of autonomous diagnostic systems in dentistry.

Keywords: Teeth Segmentation, Deep Learning, Oral Health, X-ray Images.

1. Introduction

The interpretation of dental images is critical for dentistry identity verification and oral healthcare. There are two types of dental imaging: radiography and color-based intraoral camera images [1]. Although dental X-ray images are hazardous, they are more commonly used to diagnose mouth problems such as cysts and caries, whereas color-based images are used less frequently in the oral healthcare field [2]. There are typically three types of X-ray images: a) Bitewing X-rays indicate specific tooth areas on the upper and lower jaws. The radiographic scans are used to detect gum disease and interproximal caries. b) Periapical X-ray images show the whole tooth anatomy, particularly the enamel layer and the gum regions. All irregular modifications in the root canal or bone around the area can often be identified with their assistance. c) Panoramic images are used to perform X-ray scans of the entire mouth, including gums and teeth. These types of images are widely utilized [3]. Due to the relatively small differences between the desired object and the background, the algorithm struggles to identify distinct borders in low contrast images. Delineation becomes difficult as a result of the hazy boundaries and transfer into neighboring areas. On the other hand, noise can mimic or obscure real structural elements by producing erratic variations in pixel intensity. Consequently, there is a higher chance of false negatives (the model overlooks actual structures) and false positives (the model finds non-existent structures).

DOI: https://doi.org/10.36548/jiip.2025.3.023
Received: 29.07.2025, received in revised form: 02.09.2025, accepted: 19.09.2025, published: 30.09.2025

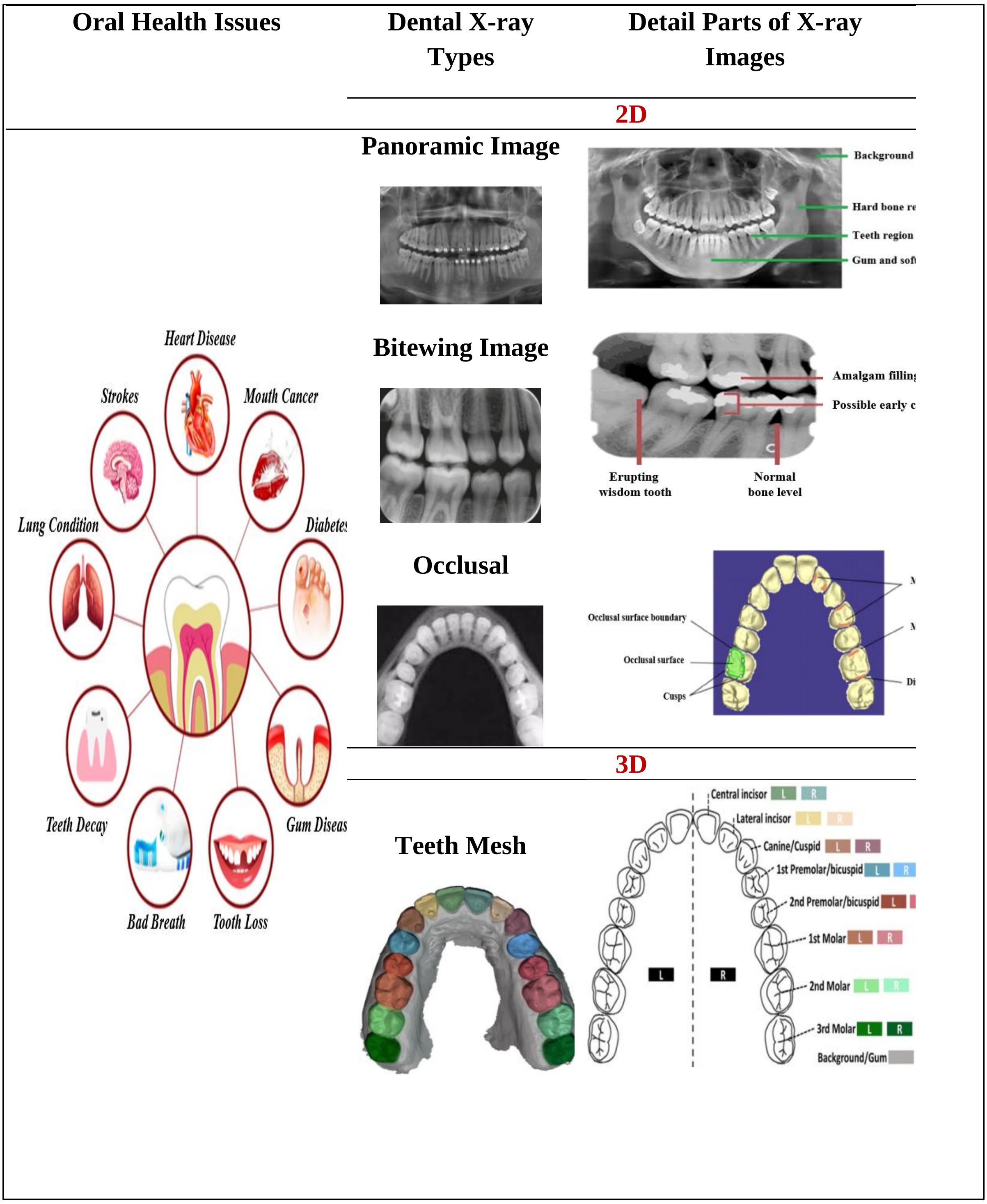

Figure 1. Oral Health Problems with Teeth, Various Kinds of Dental X-ray Images, and their Components

Low contrast and noise reduce the signal-to-noise ratio, diminishing intensity-driven segmentation precision. To counter these issues, many preprocessing techniques can be employed, such as contrast enhancement (e.g., CLAHE), noise removal filters, and data-trained models for characterizing various levels of noise and contrast in clinical settings. Dental health problems, such as cavities, gum disease, tooth sensitivity, malocclusions, and erosion of the teeth, are depicted in Figure 1. Dental X-ray images and their corresponding components are essential for diagnosing these disorders, with each type providing a different view: occlusal X-rays emphasize the upper and lower arches; panoramic X-rays provide a broad view of the jaws; bitewing X-rays reveal both upper and lower teeth in one portion; periapical X-rays reveal the entire tooth; and cone beam computed tomography (CBCT) provides detailed three-dimensional images [4]. These X-rays are taken using an X-ray machine, film or sensor, and control panel. To avoid exposing patients to unnecessary radiation, lead aprons and thyroid collars are used. With the use of these protective measures, it is possible to plan and diagnose treatments accurately. These techniques are also used in dental implant design, tooth morphology capture, and personal identification. Manual segmentation requires comprehension of dental anatomy and image software due to its high variability among different operators [5]. Interrater variability can be reduced while enhancing the precision and reliability of panoramic radiograph evaluations using an automated aid system, especially among less experienced doctors [6]. Artificial intelligence (AI) and machine learning are revolutionizing diagnostics in the medical sector. AI has been shown to aid in the segmentation, classification, and analysis of medical images in various fields, including radiology and dermatology [7]. As a result of this technological advancement, tooth segmentation based on AI has been proposed, leading to similar procedures being used in dentistry. Segmentation can be effectively achieved through the use of CNNs and other deep learning algorithms. Despite the promise of teeth segmentation using deep learning, there are several gaps in research. Firstly, extensive, diverse, and publicly accessible annotated datasets, such as panoramic X-rays and CBCT scans, do not exist. Most existing datasets are small, underrepresented in pathology, and rarely annotated at the detail instance or root level, which hinders model generalization. Secondly, advanced methods are predominantly derived from 2D variants of UNet, while more advanced techniques, such as 3D models, transformer models, and self-supervised pretraining, are less explored. Additionally, the deployment of real-time light models for user-interactive refinement tools and privacy-preserving training methods remains an issue. Finally, the combination of multimodal images (e.g., X-rays and CBCT) and longitudinal segmentation of disease history is not well studied. Addressing these gaps could potentially lead to significant improvements in teeth segmentation systems based on deep learning in terms of accuracy, robustness, and clinical utility. The primary contributions made in this paper can be summed up as follows:

- An overview of the latest deep learning methods for segmenting teeth is presented.
- Identification of the application challenges in segmenting tooth structures on X-ray images.
- Assessment of the effectiveness of segmenting tooth structural features in diagnosing oral diseases.

The paper is organized as follows: Section 2 presents background and related work. A thorough explanation of the teeth segmentation methodology is provided in Section 3. Section 4 presents the discussion and future directions. In Section 5, the paper is concluded.

2. Related Work

Segmentation of teeth is crucial for identifying and treating oral diseases as it facilitates surgical planning and tooth boundary delineation. The World Health Organization reports that oral illnesses rank among the most serious health problems in the world, causing pain, discomfort, disfigurement, and even death for people of all ages and genders [8]. According to the Global Burden of Disease 2019 report, oral diseases affect 3.5 billion people worldwide, with dental caries leading the way. Oral health issues are frequently outside the purview of universal health coverage and can be expensive to treat [9]. The ability to obtain real-time information about tooth movement and root depth is crucial for determining a patient's alignment and speeding up orthodontic treatment. An X-ray panoramic image of the mouth is produced by segmenting each tooth; this process can also be used to estimate the patients age, identify a suspect, and examine hidden structures in the mouth [10-11]. Moreover, dental imaging methods that offer a broad perspective of the mouth cavity include panoramic radiography, which makes the teeth, jawbones, and surrounding structures more visible. Dentists can examine the entire mouth and identify dental diseases such as cavities, caries, gum disease, damaged or fractured teeth, and oral cancer in addition to seeing panoramic X-ray images [12].

In many studies, specialized preprocessing procedures are used to ensure dataset consistency, especially when images are acquired from various sources with different resolutions and contrast ranges. A common method of preprocessing is resizing images to a specific resolution to ensure that all inputs are of the same dimension as the network, normalizing pixel values to a uniform range for effective model training, and enhancing tooth border contrast and clarity through histogram equalization or contrast-limited adaptive histogram equalization (CLAHE). A number of noise-reducing techniques, such as Gaussian filtering or non-local means denoising, have been developed to reduce background artifacts, while cropping or region-of-interest capture ensures that the dental region is captured rather than unnecessary areas. A number of data augmentation methods are used to improve robustness, such as rotation, flipping, and brightening. Segmentation accuracy directly depends on these processes; comparing image resolutions and intensities minimizes domain variability, contrast enhancement maximizes edge detection with regard to manual annotation and predictive learning, and reducing noise minimizes false boundary estimation. Several studies have demonstrated that preprocessing improves Dice and IoU scores, reduces prediction variability, and allows the model to generalize to previously unreported clinical data. Several algorithms have been attempted to develop an automatic segmentation algorithm that can accurately segment teeth. Dental panoramic X-rays have noisy and low-contrast boundaries, which make segmenting teeth difficult. In teeth segmentation, overlapping anatomical features, such as teeth with close contacts, overlapping crowns in X-rays, or superimposed roots in panoramic and CBCT images, present a major challenge because they hinder the visibility of clean boundaries. Several methods are reviewed that address this issue in combination with architecture design, preprocessing, and postprocessing. In architectural terms, many models utilize multi-scale feature extraction (e.g., U-Net with skip connections, attention gates, or pyramid pooling) to help the network differentiate closely positioned structures by capturing local edge details as well as contextual information. A summary of the advances made toward accurately segmenting teeth on panoramic radiographs can be found in Table 1.

Table 1. An Overview of the Limitations and Previously Published Techniques for Segmenting Teeth

Year	Author	Deep learning technique	Limitations
2018	Jader et al. [17]	Segmenting instances in panoramic X-ray images	Difficulties with neighboring and overlapping teeth.

2018	Zhang et al. [18]	Cascade network structure.	Ineffective for teeth that have serious diseases.
2019	Koch et al. [19]	U-Net for segmenting dental X-ray panoramic radiography	Segmenting teeth with complicated features or abnormalities can be challenging.
2020	Lee et al. [20]	Deep convolutional neural network	Limitations while working with images that are noisy or of low quality.
2020	Muresan et al. [21]	Techniques for deep learning and image processing	Dental issues are not well-represented in the training data.
2020	Zhao et al. [22]	Two Stage Attention Segmentation Network (TSASNet)	Ineffective when using teeth of odd sizes or shapes
2021	Kong et al. [23]	Encoder-Decoder Network	Difficulty with low-quality or artifacts-containing radiographs
2022	Shubhangi et al. [27]	CNNs and traditional image processing techniques	Computationally costly, which presents difficulties for real-time applications.
2022	Rohrer et al. [29]	Restorations in dentistry that use the U-net model.	The technique with constrained margin conditions did not seek to create clinically relevant models.
2023	Arora et al. [25]	Architecture using multimodal encoders	Limited to semantic segmentation.
2023	Kanwal et al. [26]	Mask Transformer Based Networks	Computational complexity for real-time applications
2023	Almalki et al. [24]	Techniques for self-supervised learning like UM-MAE and SimMIM	Parameter fine-tuning significantly impacts segmentation performance, including mask ratio and pre-training epochs.
2023	Hou et al. [28]	U-net with units for attention and a dense skip connection	Insufficient performance analysis on publicly available datasets makes it difficult to draw meaningful comparisons.
2023	Rubiu et al. [30]	Mask regional convolutional neural network	A larger and more variable dataset is necessary to improve the segmentation method's generalization and usability.

2023	Cho et al. [42]	Deep learning based multi-step model	Computational complexity for real-time applications
2023	Ghafoor et al. [43]	Swin-Transformers and Teeth Attention Model	A more comprehensive look at dental health issues
2024	Zannah et al. [32]	Variant U-net architectures	Depends on conventional CNN techniques
2024	Wang et al. [33]	Multi-step 3D U-net architecture	Increase in computational time for tooth segmentation
2024	Lucas et al. [34]	Dilated Tooth SegNet for 3D Dental Meshes	Lacks performance analysis due to data imbalance
2024	Jung et al. [35]	Networks for Transformer Feature Aggregation and Weighted Sparse Convolution.	Fails to capture local features
2025	Sinard et al. [41]	Four Deep Learning-Based Methods	Accuracy varied due to the presence of impacted teeth.
2025	Mou et al. [46]	Principal component analysis-based generation of bounding boxes	The segmentation method is general and useful with a larger and more diverse dataset
2025	Jose et al. [47]	Conditioned Heatmap Regression Network	Fails in the performance of the module in complex cases
2025	Lei et al. [49]	Teeth Generator for 3D dental data	The complexity of computation in real-time applications

The availability of dental equipment, including metal racks and implants, and the range of dental problems that patients encounter makes precise tooth segmentation challenging [13]. Also, the effectiveness of dental segmentation techniques that depend on manual or semi-automatic methods mostly depends on the dentist's skill and is frequently subjective, expensive, and time-consuming. Furthermore, segmentation becomes much more challenging in low-quality image situations. Given these difficulties, developing an autonomous, accurate, and effective teeth segmentation technique is essential [14]. A technique for more thorough and precise segmentation of teeth and oral tissues is panoptic segmentation, which combines semantic segmentation (classifying and identifying objects in images) with instance segmentation (isolating specific instances) [15]. Much research has shown that panoptic segmentation improves deep-learning models [16]. Jader et al. [17] proposed instance segmentation to segment teeth in panoramic X-ray images. This approach did not consider other problems besides missing teeth and dentures. Zhang et al. [18] used two deep learning techniques, region-based fully convolutional networks (R-FCN) and Faster R-CNN, to classify and detect decay in teeth. In [19], an FCN and a U-Net architecture were used to semantically segment dental panoramic radiographs. They investigated methods like data uniformity, bootstrapping low-quality annotations, test-time augmentation, and network ensembling to enhance segmentation performance. Lee et al. [20] employed a training set of 1024 radiographs created from 30 radiographs utilizing rotation, flipping, Gaussian blur, and shear transformation methods. They used a fully deep learning approach to identify and locate tooth structures by optimizing the Mask R-CNN model. Muresan et al. [21] presented a novel method for automatically detecting teeth and identifying dental problems using panoramic radiography. They used image pre-processing methods and trained a CNN model on the gathered data to improve segmentation. Zhao et al. [22] introduced a two-stage, dual-stage attention segmentation model to tackle issues like fuzzy tooth boundaries in panoramic X-rays taken in dentistry which are brought on by low contrast and intensity distribution. Kong et al. [23] substantially contributed to the scientific community by making 2602 panoramic dental X-ray images publicly available. This dataset contains expertly annotated segmentation masks for every image significantly, enhancing its value. Almalki et al. [24] improved the efficiency of their models and comprehended a small number of dental radiographs. Arora et al. [25] developed a method to extract features from panoramic radiographs using a multimodal encoder-based architecture. Using the retrieved features, the segmentation mask was finalized by deconvolution. Kanwal et al. [26] used a mask transformer network to separate teeth by combining the outcomes of instance segmentation with background semantic segmentation. Shubhangi et al. [27] used a histogram-based plurality vote method to distinguish and classify teeth in their study. Hou et al. [28] introduced a modified U-Net architecture for the segmentation of teeth. The encoder and decoder combine Squeeze-Excitation Modules with dense skip connections to overcome the semantic gap. Rohrer et al. [29] used the U-net model to segment broad panoramic X-ray images representing dental restorations. A model trained on rectangular tiled panoramic sections would outperform one trained on the full image. Rubiu et al. [30] developed a new algorithm that allows for segmenting dental X-rays into different teeth segments. An instance segmentation model was trained using a Mask Region-based Convolutional Neural Network (Mask-RCNN) architecture. Lin et al. [31] propose lightweight deep-learning methods to segment dental X-ray images for deployment on edge devices, like dental imaging systems. Zannah et al. [32] investigated the performance of different U-Net designs for dental image segmentation. The following six variations of the U-Net architecture are analysed: Vanilla, Dense, Attention, SE, Residual, and R2 U-Net. In [33], it was proposed that the 3D U-Net pipeline would be used for automated tooth segmentation. A time and accuracy assessment was conducted to determine the model's performance. Lucas et al. [34] introduced dilated edge convolution, which extends the network's receptive field to enable it to learn further distant features. As a result, segmentation results are improved, especially for complex and challenging cases. Jang et al. [42] present a method for fully automating the classification of 3D distinct teeth using dental CBCT images. Gafoor et al. [43] present a novel Teeth Attention Block component that combines an M-Net-like structure, Swin Transformers, and a novel context-dependent structure for the segmentation of multiple classes of teeth. Kunzo et al. [44] use the resultant heatmap and subsequent feature maps of a keypoint identification system to guide the segmentation procedure. Dai et al. [45] present a task-oriented Masked Auto-Encoder methodology for efficiently using vast volumes of unlabeled data to accomplish accurate tooth segmentation with minimal labeled data. Mou et al. [46] used an encoder-decoder-based structure strengthened with a grid-aware attention gate and skip connections. Furthermore, they present oriented bounding box synthesis using principal component analysis for an accurate tooth orientation estimate. Jose et al. [47] present a conditioned heatmap regression network (CHaRNet), the first entirely integrated deep learning framework for tooth landmark recognition in 3D intraoral images. Despite standard two-stage procedures, which segment teeth before detecting landmarks, CHaRNet operates directly on the provided feature cloud, thus minimizing complexity and computing overhead. Zhu et al. [48] present ViSTooth, a visualization tool that visualizes tooth segmentation on dental panoramic radiographs. Researchers used Mask R-CNN to segment teeth, followed by a set of domain metrics to measure the effectiveness of tooth segmentation, including tooth shape, tooth angle, and tooth position. Lei et al. [49] propose enabling cascade tooth setup networks such as Teeth Generator which synthesizes 3D teeth models pre- and post-orthodontic using a two-stage framework. Ammar et al. [50] present a new framework for determining margin lines in an automated manner using deep learning. A collaborative dental laboratory contributed a dataset of incisor teeth for training the deep learning categorization model.

3. Methodology

This approach enables the model to classify each tooth or dental condition and categorize the teeth, making it appropriate for clinical decision-support procedures and automated oral assessment. Furthermore, acquiring tooth segmentation data entails gathering labels (such as segmentation masks that delineate the boundaries of teeth in these images) and image information (such as dental X-rays, intraoral scans, or 3D scans). Figure 2 shows the initial stage of gathering and outlining data for tooth segmentation, and the following summarizes each stage.

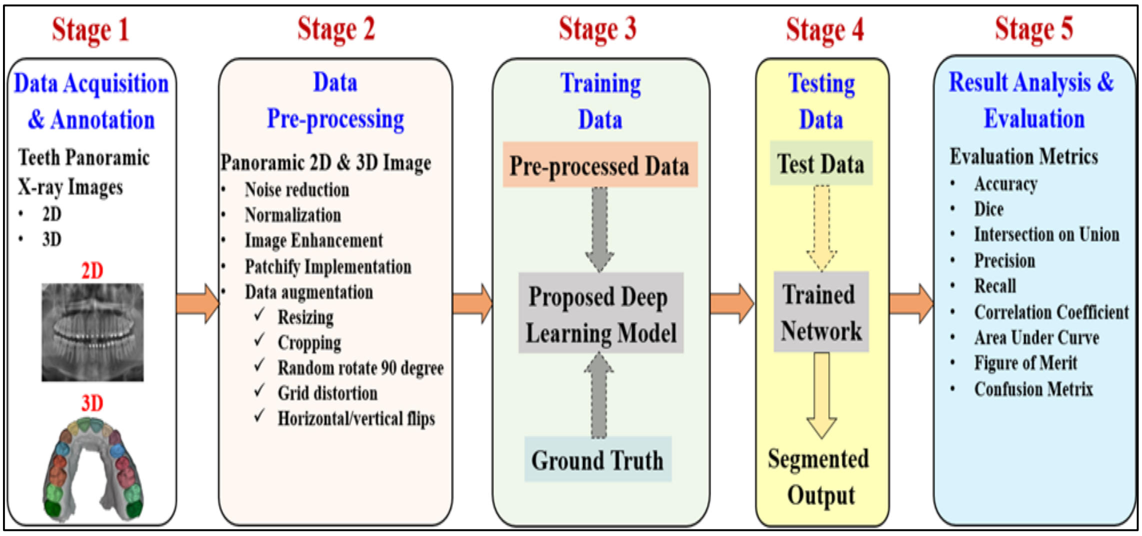

Figure 2. Overall Stages of the Proposed Project for Teeth Segmentation and Classification

3.1 Data Acquisition & Annotation

For the segmentation model to be trained, a large number of dental images will be needed. In order to develop an effective model, it is imperative to have a large and diverse amount of this data.

➢ **Types of Dental Imaging**

- **Dental Panoramic X-ray Images:** These two-dimensional pictures are frequently used in dentistry. They can display the complete set of teeth or highlight a particular one.

- **Intraoral Scans:** 3D imaging is accomplished with intraoral scanners like iTero or Trios. These types of scans produce smooth, three-dimensional images of the teeth and gums.

- **Cone beam CT (CBCT):** specialized X-ray equipment produces three-dimensional images of the teeth and surrounding tissues.

- **Photographic images:** high-quality pictures of teeth that are typically used in cosmetic dentistry.

➢ **Sources for Dental Image Data**

- **Public Datasets:** Look for dental datasets that are accessible to the public. Here are a few examples:

    1. 3D scans of teeth are accessible through the Stanford University 3D Scanning Repository [40].
    2. Publicly accessible datasets from medical challenges, such as the dental X-ray segment challenge, may contain dental images [38].

- **Private Dental Clinics:** In addition, organizations can work with dental clinics, academic institutions, or research groups to obtain their imaging data. They can also partner with radiology departments or imaging centers to obtain data such as 3D scans or X-rays.

➢ **Annotation (Labelling the Data)**

To mark the data during image acquisition, each image's tooth borders must be identified. Model training for deep learning requires high-quality annotations.

- **Types of Annotations for Teeth Segmentation**

    1. 2D Annotations Pixel-level segmentation masks for X-ray images will be used to create two-dimensional annotations of the tooth. This entails aligning each tooth in the image.
    2. 3D annotations: It might be necessary to split the teeth in 3D space for these annotations, which can be more challenging and time-consuming for 3D imaging methods like CBCT or intraoral scans.

3.2 Data Preprocessing

Several procedures are used to guarantee the precision and dependability of the input data before it is sent to a deep learning or machine learning model for teeth segmentation. This process is required to obtain accurate segmentation results. This is a thorough method of data preprocessing designed specifically for tooth segmentation.

➢ Image Resizing and Standardization

- Resize Images: All the input images, such as intraoral scans, 3D images, and X-rays, should be resized to a standard size. By doing this, issues resulting from varying sizes of images are prevented. For example, rescale each image's pixel dimensions to 256×256 or 512×512 as per the model specifications.

- Normalization: By dividing pixel values by 255, pixel values can be converted to a uniform range, e.g., [0, 1] or [-1, 1].

- Histogram equalization: Histogram equalization can be used on X-ray images to enhance contrast, emphasize teeth edges, and enhance the model's capability to distinguish between teeth and background noise.

- Augmentation: Split the dataset into training, validation, and testing sets to evaluate its predictive accuracy. Rotation, scaling, flipping, and translation of the teeth to cover position changes along with photometric transformations like brightness, contrast, and gamma adjustments to compensate for differences in X-ray exposure are some traditional ways of augmentation. Anatomical variability is sometimes simulated by elastic deformation. Rotations, flipping, and scaling are employed in dental imaging to mimic patient positioning variations as well as anatomical orientations. Contrast adjustment and Gaussian noise were applied to mimic exposure level variations and image conditions between X-ray and CBCT. By reducing overfitting, ensuring consistent performance across different imaging modalities, and generalizing to unseen data, these improvements strengthen the model's robustness.

- Weighting Strategies: The loss functions employ weighting strategies, such as dice loss or class-weighted cross-entropy, to more severely penalize underrepresented tooth classes compared to overrepresented ones (e.g., background pixels). As a result, the network learns equally across all tooth categories without favoring the most common ones

3.3 Training Analysis

To train a model to recognize and separate teeth in dental images (such as X-rays, 3D scans, or intraoral images), data for training must be provided. Usually, input images and their matching ground truth annotations make up the training data.

- **Epochs:** The number of times the model will run through the training set. Values typically range from 50 to 200 epochs, depending on the complexity and size of the dataset.

- **Batch size:** The number of samples that are processed prior to the internal parameters of the model being updated. For segmentation work, a batch size of 16 or 32 is frequently utilized.

- **Learning rate:** An important hyperparameter that regulates the model's rate of learning. The model could fail to converge if it is too large, and training will be poor if it is too small.

- **Validation Data:** To prevent overfitting, validation data must differ from training data for monitoring the models performance.

Since it determines when a model learns from its errors, the loss function is essential in segmentation tasks. One can select from a variety of loss functions that are appropriate for segmentation tasks because it is a pixel-wise classification problem. Typical loss functions are:

- **Binary Cross Entropy Loss:** For binary segmentation (teeth vs. background).

- **Categorical Cross-Entropy Loss:** For multi-class segmentation (e.g., segmenting different types of teeth).

- **Dice Loss:** It measures the overlap between ground truth and projected regions, which is important when working with unbalanced datasets, especially in medical imaging. It is frequently used for segmentation tasks.
- **Dice Coefficient:** Frequently employed as a segmentation quality metric when combined with loss functions.

3.4 Testing Analysis

For proper evaluation, it is important to ensure that the testing data for tooth segmentation is appropriately prepared, preprocessed, and aligned with the training data. It is necessary to evaluate the trained models capacity for generalization using a testing dataset that is separate from the training dataset.

➢ Testing with Various Image Types

- **Different Teeth Positions:** Test for variations in the occlusions, angles, or placements of the teeth (e.g., whole vs. partial teeth).
- **Noise and Artifacts:** To determine whether or not the design exists, test it on images with different noise levels, such as unclear images, low contrast, or dental artifacts.
- **Diverse Data:** To determine how well the model makes generalizations, test it using images of various patients or demographics.

3.5 Analysis & Evaluation

The next step is to assess the manner in which the trained model performs after integrating and pre-processing the testing data. For segmentation tasks, typical metrics for assessment include:

- **Dice Similarity Coefficient (DSC):** An estimate of how much the segmentation mask overlaps with the ground truth. This method is commonly used to segment medical images.
- **Intersection over Union (IoU):** In this measure, the ground reality and the predictions are compared to determine the degree of overlap.
- For categorization to assess false positives and negatives, precision and recall are also important.
    1. **Precision:** The proportion of tooth regions with accurate predictions
    2. **Recall:** The proportion of real tooth regions that were accurately predicted
    3. **Accuracy:** The percentage of correctly predicted pixels.
- **Mean Absolute Error (MAE):** An analysis of the differences between the reference image and the predicted segmentation.
- **Hausdorff Distance:** The largest difference between the ground truth and expected boundaries is determined by the Hausdorff Distance. This is particularly crucial for determining the segmentation's topology.

➢ Visual Inspection

- **Combine expected and ground truth masks:** For a visual evaluation, overlap the original images with the predicted segmentation masks. This allows us to assess when the model correctly divides the tooth regions.

- **Check for boundary accuracy:** Make sure that the generated teeth masking' bounds correspond to the ground truth's physical tooth boundaries.

3.6 Challenges in Teeth Segmentation

Deep learning facilitates robust methods and tools for tooth segmentation that enhance accuracy, efficiency, and scalability. Previously, manual or rule-based segmentation of teeth was often tedious, subject to variability, and error-prone. Deep learning methods over the last couple of years have significantly enhanced the automation and augmentation of this process, such as CNNs. The field of teeth segmentation still encounters several challenges and research gaps despite significant improvements with deep learning. In teeth segmentation methods, overlapping anatomical structures, like teeth with tight contacts, overlapping crowns in X-rays, or superimposed roots in panoramic and CBCT images, pose a significant challenge because they diminish the visibility of distinct boundaries. The discussed approaches mitigate this problem by using a combination of architecture design, preprocessing, and post-processing solutions. In most models, multi-scale features are learned (e.g., skip connections, attention gates, or pyramid pooling) to capture local edge detail as well as more general contextual detail, enabling the network to separate closely located structures. Further, teeth segmentation also suffers from issues like incomplete or imbalanced data, high-cost annotations, and limited generalization across modalities. The problem can be alleviated by creating large, heterogeneous, and open datasets and applying semi-weakly supervised learning to minimize labeling processes. The system's robustness can further be improved through techniques like augmentation and domain adaptation. All these factors are crucial to understand for a trustworthy clinical application. Table 2 indicates the current state of research in the suggested research gaps.

Table 2. The Status of Research in the Proposed Research Gaps

Quantification Parameters	Challenges	Research Gaps
3D Teeth Segmentation	It has been found that current research focuses mostly on 2D segmentation, but segmenting teeth in 3D scans poses additional challenges due to increased data complexity and the need to reconstruct accurate surfaces.	Currently, no 3D segmentation techniques can handle the intricate details of teeth in 3D space. There is potential for further exploring methods like 3D CNNs or voxel-based learning.
Multi-task Learning (MTL) for Teeth Diagnosis	There are several tasks related to teeth segmentation, including dental disease detection, tooth classification, and occlusion analysis.	Multitask learning approaches to analyze teeth segmentation, disease detection, or tooth classification, could enhance AI systems' diagnostic abilities.

Limited Annotated Data	There is a lack of high-quality annotated dental images (X-rays, 3D scans, and intraoral images) owing to manual annotation and expert knowledge required.	Annotated datasets need to be developed in more comprehensive and diverse ways. Data augmentation techniques may include generating synthetic data using methods like Generative Adversarial Networks (GANs) or semi-supervised learning procedures to reduce reliance on labeled data.
Robustness to Artifacts and Noise	There can be noise in dental X-rays or intraoral images, and artifacts such as motion blur or misalignment can negatively affect a segmentation.	Segmentation performance can be improved in real-world conditions by including noise-resistant models that can tolerate common artifacts in dental imaging.
Segmentation in Complex and Crowded Dental Structures	It can be difficult to distinguish the boundaries between teeth, especially in patients with complex dental conditions (e.g., overcrowding, missing teeth, or implants.	New architectures, such as Transformer-based models or advanced boundary detection techniques, will be needed to accurately segment overlapping or tightly packed teeth.
Interpretability and Explainability	For medical applications, deep learning models tend to be seen as "black boxes," making it difficult to interpret how segmentation decisions are made.	To increase trust and enable clinical adoption, it is imperative that AI can explain why certain predictions are made in dental image segmentation.

Addressing these research gaps through more advanced algorithms, diverse datasets, and multi-modal approaches will be critical to move toward scalable, practical, and reliable AI-based dental solutions.

4. Discussion and Future Directions

4.1 Dataset for Teeth analysis

Teeth segmentation datasets are crucial for developing and evaluating deep learning models in dental image analysis. These datasets provide ground truth annotations of teeth in dental images, enabling models to learn how to segment individual teeth or anatomical structures within the mouth. Table 3 shows some commonly used teeth segmentation datasets for deep learning.

Table 3. The Status of Teeth Segmentation Datasets for Deep Learning

Dataset	# of Images	Description
UFBA-UESC	The data collection consists of 4000 panoramic images, of which 3150 were marked up using the Human-in-The-	This dataset contains dental images used for developing and evaluating techniques for dental image analysis

Dataset [37]	Loop concept, and 850 were manually labeled from scratch. Only 2000 radiographs (650 from scratch and 1350 using HITL) have their annotations made public; the remaining 2000 are used to test models on our OdontoAI platform.	and segmentation. It results from an association between the Federal University of Bahia (UFBA) and the State University of Santa Cruz (UESC), both from Brazil.
A Dual-labeled Dataset [38]	The collection includes 2,000 panoramic radiographs in total. The Federation Dentaire International (FDI) notation was used to number the teeth, with 91 denoting supernumerary teeth and 11 to 48 otherwise. There were 33 different numbering labels used in all.	The "Labeled Teeth Dataset," as it is commonly known, is a collection of intraoral images of dental. It generates pixel-level annotations for individual teeth in dental images. It is generally used for teeth segmentation and other dental-related tasks, such as automated treatment planning and diagnosis.
Dental CBCT Dataset [39]	The dataset includes 329 volumetric CBCT scans of the oral cavity, including data from 169 people and 8 panoramic radiographs, each representing a distinct patient. In addition, a total of 5401 teeth, or 188 CBCT files, are listed in the 16203 periapical radiographs that are available, each with three distinct aspect views.	Dental imaging frequently uses cone-beam computed tomography (CBCT) images included in this dataset. It assists in developing 3D segmentation algorithms by segmenting teeth, gums, and other components within the jaw.
Teeth3DS Dataset [40]	To create Teeth3DS, dental surgeons and orthodontists with over five years of expertise obtained and verified 1800 intraoral scans (23999 annotated teeth) of 900 individuals, encompassing the upper and lower jaws separately.	As part of 3DTeethSeg, it is designed to advance the research area and stimulate the 3D vision community to delve deeper into intra-oral 3D scanning analysis, including teeth identification, segmentation, labeling, and modeling.

4.2 Performance Evaluation Metrics for Teeth Analysis

Evaluation metrics are crucial for teeth segmentation because they provide objective and quantitative means to assess the performance of segmentation algorithms [36]. Teeth segmentation is important in dental imaging because it assists in activities including diagnosis, treatment planning, and dental surgery. In addition, investigations have assessed segmentation consistency across distinct tooth structures at both the inter- and intra-class levels. A design's inter-class consistency relates to its capability to segment multiple tooth types with precision and similarity, regardless of shape, size, or location, especially incisors, canines, and premolars. A performance parameter, such as DSC or IoU, is often calculated for each tooth variety to be assessed to detect bias. In contrast, intra-class uniformity measures the model's ability to segment teeth of the identical type across various patients and imaging situations, making sure segmentation performance remains consistent irrespective of position deviations, restorations, or contrast values on X-rays or CBCT images. In numerous studies, researchers utilize statistical methods like ANOVA or non-parametric tests to determine whether differences between or within courses are of statistical significance. In addition, qualitative expert assessments can help determine if interclass and intraclass segmentations meet clinical expectations, particularly when similar features or diseases are present. The use of both quantitative and qualitative methodologies makes sure the approach to segmentation is not only generally accurate but also dependable and balanced across various teeth forms. To assess mask effectiveness, dentists often employ accuracy and recall to compare predicted masks to ground truth annotations, as well as boundary-driven measurements like Hausdorff Distances (HD) for border alignment and DSC, and IoU for prediction overlaps with ground truth. Numerical assessments of segmentation results are performed (e.g., precision and recall for accuracy and completeness, boundary-based assessments such as HD for edge alignment, DSC and IoU for connection between prediction and ground truth), as well as visual inspection with original dental X-rays or CBCT images superimposed to make sure tooth edges are correctly recognized and typical mistakes (such as under- or over-segmentation) are reduced. In conventional segmentation, DSC and Jaccard indexes (JI) are commonly employed to quantify overlap accuracy, whilst precision and recall are utilized to address false positives and false negatives in unbalanced data sets. There is a discussion of boundary-driven metrics, particularly HD, for assessing errors along teeth borders where precise structural accuracy is essential. The DSC and JI are useful indicators of overall overlap, but they can be unreliable when borders are wrong. While precision and recall are essential for addressing class imbalances, spatial accuracy is frequently disregarded. Using boundary-based measures, such as HD, can detect edge deviations, but can become excessively susceptible to outliers. As a result, it is recommended to employ a combination of measures to assess segmentation efficacy. Table 4 presents several commonly used evaluation metrics for teeth segmentation.

Table 4. An Overview of the Teeth Segmentation Validation Measures

Metric	Description	Method
Dice Similarity Coefficient (DSC)	Analyzes the overlap between the reference segmentation and the predicted segmentation. A higher value indicates a greater overlap.	$Dice = \frac{2TP}{2TP + FP + FN}$
Accuracy	Determines how many pixels were correctly identified out of all the pixels.	$Accuracy = \frac{TP + TN}{TP + TN + FN + FP}$
Precision	Measures the percentage of the retrieved instances that are relevant.	$Precision = \frac{TP}{TP + FP}$
Recall (Sensitivity)	It measures the number of relevant instances retrieved over the total number of relevant instances.	$Recall = \frac{TP}{TP + FN}$
Intersection over Union (IoU)	By comparing ground truth and predicted areas, false negatives and false positives are penalized.	$IoU = \frac{TP}{TP + FP + FN}$
F1 Score	Harmonic means of Precision and Recall, offering a balance between both.	$F1\ Score = 2\frac{Precision.Recall}{Precision + Recall}$

Specificity	Basically, the True Negative Rate measures the accuracy of negative pixels in images.	$Specificity = \frac{TN}{TN + FP} (* 100)$
Hausdorff Distance	Calculates the distance between any point in the predicted segmentation and the reference boundary.	$H(A, B) = max\big(h(A, B), h(B, A)\big)$ *h (A, B) ranks points of A according to their nearest points of B and uses the most mismatched points* $h(A, B) = \max_{a \in A} \min_{b \in B} \lVert a - b \rVert$
Mean Absolute Error (MAE)	Compares the ground truth with the predictions to find the average absolute difference between the segmentation boundaries.	$MAE = {}^{1}/_{n} \sum_{i=1}^{n} \lvert Y_{actual} - Y_{pred} \rvert$

Table 5 presents a review of the reviewed papers, presenting deep learning-based teeth structure segmentation outcomes using evaluation metrics such as accuracy, IoU, F1 score, dice, and recall. Kong et al. [23] provide superior accuracy results than previous approaches utilizing the dental clinic dataset. To extract further semantic information from depth and breadth, the author replaced the convolution layer with the Inception-ResNet block in the multipath feature extractor and the residual block in the encoder. Lucas et al. [34] presented dilated edge convolution, a network operating style that broadened the network's receptive range and improved its ability to acquire information farther away, making IoU and Dice outcomes better by using the Teeth3DS dataset. Rohrer et al. [29] introduced that training CNNs on smaller, evenly spaced rectangular image crops (tiles) circumvents the information loss caused by downsizing and enhances model performance.

Table 5. An Overview of the Results of Deep Learning Techniques for Segmenting Teeth

Year	Author	Dataset	Accuracy	IoU	F1 score	Dice	Recall
2018	Jader et al. [17]	UFBA-UESC	0.98	-	0.88	-	0.84
2018	Zhang et al. [18]	Dental Clinic			0.96		0.96
2019	Koch et al. [19]	UFBA-UESC	0.94	-	-	0.93	-
2020	Lee et al. [20]	UFBA-UESC	-	0.87	0.87	-	0.89
2020	Muresan et al. [21]	Dental Clinic	0.89	-	0.93	-	0.91
2020	Zhao et al. [22]	UFBA-UESC	0.96	-	-	0.92	0.93
2021	Kong et al. [23]	Dental Clinic	0.99	-	0.98	-	-
2022	Rohrer et al. [29]	Dental Clinic	-	0.93	0.97	-	-
2023	Kanwal et al. [26]	UFBA-UESC	0.97	-	0.93	-	-
2023	Almalki et al. [24]	TNDRS	0.90	-	0.88	-	-
2023	Hou et al. [28]	Dental Clinic	0.95	-	-	0.88	0.94
2023	Rubiu et al. [30]	Tufts Dental	0.98	-	-	0.87	-
2023	Cho et al. [42]	Dental Clinic	-	-	0.93	0.96	0.90
2023	Ghafoor et al. [43]	Dental Clinic	0.97	-	-	0.91	0.93
2024	Zannah et al. [32]	Dental Clinic	0.95	0.88	0.90	0.90	-
2024	Wang et al. [33]	Dental Clinic	-	0.90	-	0.94	-

2024	Lucas et al. [34]	Teeth3DS	0.97	0.95	-	0.97	-
2024	Jung et al. [35]	3D Dental	0.93	0.88	-	-	-
2024	Dai et al. [45]	Dental Clinic	-	-	-	0.89	0.88
2025	Sinard et al. [41]	Dental Clinic	-	-	-	0.95	-
2025	Mou et al. [46]	Dental Neglect Scale	-	0.82	-	0.90	0.90
2025	Zhu et al. [47]	Dental Clinic	-	0.75	0.79	-	0.83
2025	Ammar et al. [50]	3D Dental	0.97	-	-	0.95	-

Zhang et al. [18] introduced a novel technique that uses a label tree to assign multiple labels to each tooth and break down the process to address the lack of data. Further, teeth segmentation using deep learning is a rapidly advancing field, with many exciting future directions. These advancements are driven by the growing potential of AI, improved algorithms, and specialized architectures designed for medical imaging. Current approaches mostly rely on 2D imaging techniques, but the future will rely more on 3D models. These can analyze volumetric data from CBCT to better understand the spatial relationships between teeth, their roots, and surrounding bone structures. Figure 3 compares the performance of the surveyed methods across publicly available datasets for segmenting the structure of teeth.

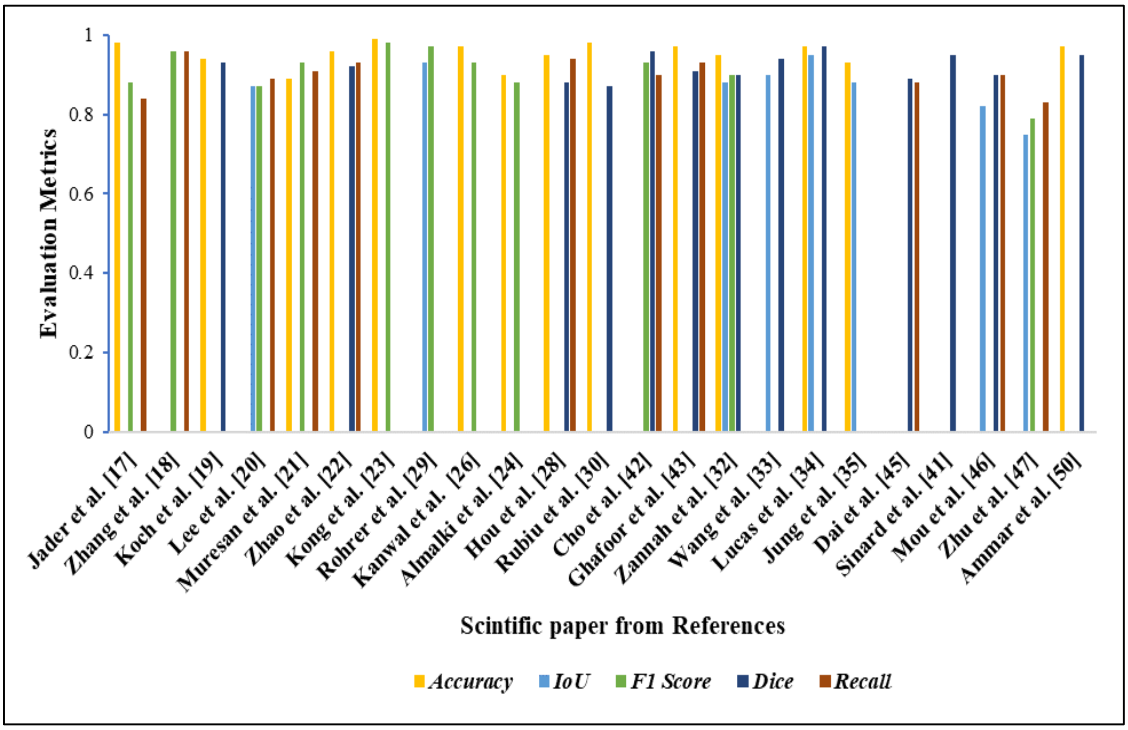

Figure 3. Results of a Deep Learning Study on Segmenting Tooth Structures

Future systems may incorporate augmented reality or virtual reality technology to visualize segmented teeth in 3D, helping clinicians make more informed decisions during diagnosis or procedures. The future of deep learning in teeth segmentation holds significant promise, with innovations in architecture, data integration, and real-time applications. By combining these advances with stronger datasets and clinical collaboration, these technologies will improve diagnostic accuracy and enhance personalized care, enabling a future of more efficient and precise dental treatments.

5. Conclusion

In the face of recent advancements in deep learning, many provocations remain that provide strong direction for better research. To popularize better models, large, diverse, and publicly available datasets are required, along with panoramic X-rays, CBCTs, intraoral scans, appliances, and pathologies. Foremost, integrating advanced models such as self-supervised learning and transformer-based architectures is essential, especially in low-contrast and noisy images. Moreover, domain adaptation and variability estimation must be investigated to counteract performance drops between patient scanners, groups, and clinical settings. As part of this survey, we reviewed the state of the art in research on tooth structure and its impact on oral cavity disease diagnosis. Segmenting teeth is challenging due to the noisy setting and low contrast of the images. To address these difficulties, several models for segmentation and oral disease diagnosis have been proposed with varying degrees of complexity. Precise results have been developed over decades. Recently, there has been a large annotated dental dataset, standardized metrics, and a need for the generalization of methods across imaging modalities, as well as challenges in accurately segmenting overlapping anatomical structures. Future research should focus on large-scale, standardized dental image repositories. Domain adaptation strategies should be developed to enhance cross-modality performance and reduce annotation costs. In addition, an explainable AI perspective should be explored to build trust in automated diagnostic systems.

Acknowledgement

This study received funding from the Anusandhan National Research Foundation, Government of India, under project number ANRF/IRG/2024/000403/ENS.

References

[1] P. Ghosh, D. Bhattacharjee, M. Nasipuri, "Automatic system for plasmodium species identification from microscopic images of blood-smear samples", J. Healthc. Inform. Res. 1, no.2, (2017): 231–259.

[2] S.T. Reisine, "Dental health and public policy: the social impact of dental disease", Am J Public Health 75 (1), (1985): 27–30.

[3] E. Whaites, N. Drage, "Essentials of Dental Radiography and Radiology", Elsevier Health Sciences, (2013): 488.

[4] Shaheen E, Leite A, Alqahtani KA, Smolders A, Van Gerven A, Willems H, "A novel deep learning system for multi-class tooth segmentation and classification on cone beam computed tomography. A validation study: deep learning for teeth segmentation and classification". J Dent, 115, (2021): 103865.

[5] Reyes M, Meier R, Pereira S, Silva CA, Dahlweid FM, von Tengg-Kobligk, "On the interpretability of artificial intelligence in radiology: challenges and opportunities", Radiol Artif Intell, 2, no. 3, (2020): e190043.

[6] Carrillo-Perez F, Pecho OE, Morales JC, Paravina RD, Della Bona A, Ghinea R, "Applications of artificial intelligence in dentistry: a comprehensive review". J Esthet Restor Dent, 34, no. 1, (2022): 259–80.

[7] Tandon D, Rajawat J. “Present and future of artificial intelligence in dentistry”. J Oral Biol Craniofac Res; 10 no. 4, (2020).

[8] Silva G, Oliveira L, Pithon M “Automatic segmenting teeth in X-ray images: Trends, a novel data set, benchmarking, and future perspectives,” Expert Syst App, l107, (2018):15–31.

[9] Zannah R, Bashar M, Mushfiq RB, Chakrabarty A, Hossain S, and Jung YJ. “Semantic Segmentation on Panoramic X-ray Images Using U-Net Architectures”, IEEE Access, 12, (2024): 44598-44612.

[10] Van Dessel, J.; Nicolielo, L.P.; Huang, Y.; Coudyzer, W.; Salmon, B.; Lambrichts, I.; Maes, F.; Jacobs, R. “Automated segmentation of teeth and interproximal contact points from cone beam computed tomography images”, Dento Maxillo Facial Radiol, 44, (2015): 20140315.

[11] Al, A.; Ijaz, U.; Song, Y.J.; Lee, S.; Park, S.; Lee, K.W.; Seo, W.B.; Park, K.W.; Han, J.W.; Lee, H. “Deep learning for segmentation of 49 regions in 2D and 3D panoramic dental X-ray images”, Dento Maxillo Facial Radiol, 47, (2018): 20170389.

[12] Wang C-W, Huang C-T, Lee J-H, Li C-H, Chang S-W, Siao M-J, Lai T-M, Ibragimov B, Vrtovec T, and Ronneberger, “A benchmark for comparison of dental radiography analysis algorithms”, Med Image Anal, 31, (2016): 63–76.

[13] Singh, N.K.; Raza, K, “Progress in deep learning-based dental and maxillofacial image analysis: A systematic review”, Expert Syst. Appl, 199, (2022): 116968.

[14] Xu, X.; Chiu, M.T.; Huang, T.S.; Shi, H. “Deep affinity net: Instance segmentation via affinity”, arXiv, arXiv:2003.06849, (2020).

[15] Li, X.; Chen, D. “A survey on deep learning-based panoptic segmentation”. Digit. Signal Process. 120, (2022): 103283.

[16] Chuang, Y.; Zhang, S.; Zhao, X. “Deep learning-based panoptic segmentation: Recent advances and perspectives”, IET Image Process, 17, no. 10, (2023): 2807-2828.

[17] Jader, G.; Fontineli, J.; Ruiz, M.; Abdalla, K.; Pithon, M.; Oliveira, L. “Deep instance segmentation of teeth in panoramic X-ray images”. In Proceedings of the 2018 31st SIBGRAPI Conference on Graphics, Patterns and Images, Brazil, IEEE: Piscataway, USA, (2018): 400–407.

[18] Zhang, K.; Wu, J.; Chen, H.; Lyu, P. “An effective teeth recognition method using label tree with cascade network structure” Comput. Med. Imaging Graph, 68, (2018): 61–70.

[19] Koch, T.L.; Perslev, M.; Igel, C.; Brandt, S.S. “Accurate segmentation of dental panoramic radiographs with U-Nets”. In Proceedings of the 2019 IEEE 16th International Symposium on Biomedical Imaging, Venice, Italy, IEEE: Piscataway, NJ, USA, (2019): 15–19.

[20] Lee, J.H.; Han, S.S.; Kim, Y.H.; Lee, C.; Kim, I. “Application of a fully deep convolutional neural network to automate tooth segmentation on panoramic radiographs”, Oral Surg. Oral Med. Oral Pathol. Oral Radiol., 129, (2020): 635–642.

[21] Muresan, M.P.; Barbura, A.R.; Nedevschi, S. "Teeth Detection and Dental Problem Classification in Panoramic X-Ray Images using Deep Learning and Image Processing Techniques", IEEE 16th International Conference on Intelligent Computer Communication and Processing (ICCP), Cluj-Napoca, Romania; IEEE: Piscataway, (2020): 457–463.

[22] Zhao, Y.; Li, P.; Gao, C.; Liu, Y.; Chen, Q.; Yang, F.; Meng, D. "TSASNet: Tooth segmentation on dental panoramic X-ray images by Two-Stage Attention Segmentation Network". Knowl.-Based Syst., 206, (2020): 106338**.**

[23] Kong, Z.; Xiong, F.; Zhang, C.; Fu, Z.; Zhang, M.; Weng, J.; Fan, M. "Automated Maxillofacial Segmentation in Panoramic Dental X-Ray Images Using an Efficient Encoder-Decoder Network", IEEE Access, 8, (2020): 207822–207833**.**

[24] Almalki, A.; Latecki, L.J. "Self-Supervised Learning with Masked Image Modeling for Teeth Numbering, Detection of Dental Restorations, and Instance Segmentation in Dental Panoramic Radiographs". In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, Waikoloa, HI, USA, (2023): 5594–5603.

[25] Arora, S.; Tripathy, S.K.; Gupta, R.; Srivastava, R. "Exploiting multimodal CNN architecture for automated teeth segmentation on dental panoramic X-ray images". Proc. Inst. Mech. Eng. Part H J. Eng. Med., 237, (2023): 395–405.

[26] Kanwal M, Ur Rehman MM, Farooq MU, Chae DK. "Mask-Transformer-Based Networks for Teeth Segmentation in Panoramic Radiographs", Bioengineering (Basel), Jul 17; 10, no. 7, (2023): 843.

[27] Shubhangi, D.; Gadgay, B.; Fatima, S.; Waheed, M. "Deep Learning and Image Processing Techniques applied in Panoramic X-Ray Images for Teeth Detection and Dental Problem Classification". In Proceedings of the 2022 International Conference on Emerging Trends in Engineering and Medical Sciences (ICETEMS), Nagpur, India, 18–19 November 2022; IEEE: Piscataway, NJ, USA, (2022): 64–68.

[28] Hou, S.; Zhou, T.; Liu, Y.; Dang, P.; Lu, H.; Shi, H. Teeth U-Net: "A segmentation model of dental panoramic X-ray images for context semantics and contrast enhancement", Comput. Biol. Med. 152, (2023): 106296**.**

[29] Rohrer C, Krois J, Patel J, Meyer-Lueckel H, Rodrigues JA, Schwendicke F. "Segmentation of Dental Restorations on Panoramic Radiographs Using Deep Learning. Diagnostics", May 25;12 no. 6, (2022):1316.

[30] Rubiu G, Bologna M, Cellina M, Cè M, Sala D, Pagani R, Mattavelli E, Fazzini D, Ibba S, Papa S, "Teeth Segmentation in Panoramic Dental X-ray Using Mask Regional Convolutional Neural Network". Applied Sciences, 13, no. 13, (2023): 7947.

[31] Lin, Songyue, Xuejiang Hao, Yan Liu, Dong Yan, Jianwei Liu, and Mingjun Zhong. "Lightweight deep learning methods for panoramic dental X-ray image segmentation", Neural Computing and Applications, 35, no. 11, (2023), 8295-8306.

[32] Zannah, Rafiatul, Mubtasim Bashar, Rahil Bin Mushfiq, Amitabha Chakrabarty, Shahriar Hossain, and Yong Ju Jung. "Semantic Segmentation on Panoramic X-ray Images using U-Net Architectures", IEEE Access, (2024).

[33] Wang, Xiaotong, Khalid Ayidh Alqahtani, Tom Van den Bogaert, Sohaib Shujaat, Reinhilde Jacobs, and Eman Shaheen. "Convolutional neural network for automated tooth segmentation on intraoral scans", BMC Oral Health, 24, no. 1, (2024): 804.

[34] Krenmayr, Lucas, Reinhold von Schwerin, Daniel Schaudt, Pascal Riedel, and Alexander Hafner. "DilatedToothSegNet: Tooth Segmentation Network on 3D Dental Meshes Through Increasing Receptive Vision", Journal of Imaging Informatics in Medicine, (2024): 1-17.

[35] Jung Ahn and Y. -R. Cho, "Weighted Sparse Convolution and Transformer Feature Aggregation Networks for 3D Dental Segmentation," in IEEE Access, vol. 12, (2024): 135172-135184.

[36] Yamanakkanavar, Nagaraj, Jae Young Choi, and Bumshik Lee "MRI Segmentation and Classification of Human Brain Using Deep Learning for Diagnosis of Alzheimer's Disease: A Survey" Sensors 20, no. 11, (2020): 3243.

[37] B. Silva, L. Pinheiro, B. Sobrinho, F. Lima, B. Sobrinho, K. Abdalla, M. Pithon, P. Cury, and L. Oliveira, "OdontoAI: A human-in-the-loop labeled data set and an online platform to boost research on dental panoramic radiographs" in arXiv, (2022).

[38] Zhou, W., Lu, X., Zhao, D. "A dual-labeled dataset and fusion model for automatic teeth segmentation, numbering, and state assessment on panoramic radiographs". BMC Oral Health, 24, (2024): 1201.

[39] Huang, Y., Liu, W., Yao, C. "A multimodal dental dataset facilitating machine learning research and clinic services", Sci Data, 11, (2024): 1291.

[40] B Hamadou, A Smaoui, C Chouayakh, H Rekik, A Pujades, S Boyer, E Strippoli, J Thollot, A Setbon, H Trosset, C Ladroit, Edouard. "Teeth3DS: a benchmark for teeth segmentation and labelling from intra-oral 3D scans", arXiv:2210.06094, (2022)

[41] Sinard, E., Gajny, L., de La Dure-Molla, M., Felizardo, R. and Dot, G., Automated Cone Beam Computed Tomography Segmentation of Multiple Impacted Teeth With or Without Association to Rare Diseases: Evaluation of Four Deep Learning-Based Methods. Orthod Craniofac Res, 28, (2025): 433-440.

[42] Jang TJ, Kim KC, Cho HC, Seo JK. A Fully Automated Method for 3D Individual Tooth Identification and Segmentation in Dental CBCT. IEEE Trans Pattern Anal Mach Intell. Oct; 44, no. 1, (2023): 6562-6568.

[43] Ghafoor, S. -Y. Moon and B. Lee, "Multiclass Segmentation Using Teeth Attention Modules for Dental X-Ray Images," in IEEE Access, 11, (2023): 123891-123903.

[44] Tomas Kunzo, Viktor Kocur, Lukáš Gajdošech, Martin Madaras, "Processing and Segmentation of Human Teeth from 2D Images using Weakly Supervised Learning", arXiv:2311.07398,(2024): n.pag.

[45] P. Dai, Y. Ou, Y. Yang, Y. Liu and Y. Zhao, "Sparse Anatomical Prompt Semi-Supervised Learning with Masked Image Modeling for CBCT Tooth Segmentation," IEEE International Symposium on Biomedical Imaging (ISBI), Athens, Greece, (2024): 1-5.

[46] Deb, Mou, Madhab Deb, and Mrinal Kanti Dhar. "A Deep Learning Approach to Teeth Segmentation and Orientation from Panoramic X-Rays" Signals, no. 3, (2025): 40.

[47] Jose and Rodríguez-Ortega, Francisco Pérez-Hernández, Siham Tabik, “CHaRNet: Conditioned Heatmap Regression for Robust Dental Landmark Localization”, arXiv:2501.13073, (2025).

[48] Zhu, S., Hu, M., Pan, T. et al. ViSTooth: a visualization framework for tooth segmentation on panoramic radiograph. J Vis, (2025).

[49] Changsong Lei, Yaqian Liang, Shaofeng Wang, Jiajia Dai, Yong-Jin Liu, “TeethGenerator: A two-stage framework for paired pre- and post-orthodontic 3D dental data generation”, arXiv:2507.04685, Jan 22, (2025).

[50] Ammar Alsheghri, Ying Zhang, Farnoosh Ghadiri, Julia Keren, Farida Cheriet, Francois Guibault “Mesh-based segmentation for automated margin line generation on incisors receiving crown treatment”, Mathematics and Computers in Simulation, 239, (2025): 716-728.